Project Work House Rent Prediction In New Delhi , Name - Ashish Pratap Dwivedi

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing the Data Set

```
df = pd.read_csv(r"C:\Data Analysis Course DU\Projects\Data Analytics
Project work\makaan_data.csv")

#Check the head of DataSet

df.head()

   Sr No  Size Size_unit      Property_type          Location
Seller_name  \
0      0     2       BHK  Independent Floor       Uttam Nagar
seller
1      1     3       BHK  Independent House        Model Town
seller
2      2     2       BHK          Apartment  Sector 13 Rohini
seller
3      3     3       BHK          Apartment         DLF Farms
seller
4      4     3       BHK  Independent Floor       laxmi nagar
seller

      Seller_type Rent_price  Area_sqft          Status
Security_deposit  \
0  Verified Owner      8,500        500  Semi-Furnished
No
1  Verified Owner     48,000       1020       Furnished
No
2  Verified Owner     20,000        810     Unfurnished
No
3  Verified Owner     11,000        750  Semi-Furnished
No
4  Verified Owner     20,000       1300       Furnished
No

   Bathroom Facing_direction
0       1.0        NorthWest
1       3.0            South
2       2.0              NaN
```

```
3       1.0              NaN
4       2.0              NaN
```

Data Cleaning and Processing

```
#Dropping  the Columns
house = df.drop(columns=["Sr No","Seller_name","Security_deposit"])
house.shape
```

```
(14000, 10)
```

```
# print("--- Data Cleaning and Preprocessing ---")
# # 1. Get the initial number of rows
# initial_rows = house.shape[0]
# # 2. Drop duplicate rows
# house.drop_duplicates(inplace=True)
# # 3. Print information about dropped duplicates
# print(f"\nDropped {initial_rows - house.shape[0]} duplicate rows.")
# print(f"Shape after dropping duplicates: {house.shape}")
# # Identify duplicates
# # duplicates = df.duplicated()

# # Count the number of duplicate rows
# # duplicate_count = duplicates.sum()

# # print(f"Number of duplicate rows: {duplicate_count}")

house.shape
```

```
(14000, 10)
```

```
# Data Checking
print("INFO of Data :")
print(house.info())

print("\n")
#decsribe the data
print("Describe the Data :")
print(house.describe())

print("\n")

print("Decsribe the data including Object :")
print(house.describe(include="object"))

print("\n")
#Checking Unique Value from Each Column

print("Unique value of Each Column :")
for col in house.columns:
    print(f"-{col}: {house[col].nunique()}")
```

```
INFO of Data :
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14000 entries, 0 to 13999
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Size              14000 non-null  int64  
 1   Size_unit         14000 non-null  object 
 2   Property_type     14000 non-null  object 
 3   Location          14000 non-null  object 
 4   Seller_type       14000 non-null  object 
 5   Rent_price        14000 non-null  object 
 6   Area_sqft         14000 non-null  int64  
 7   Status            14000 non-null  object 
 8   Bathroom          6217 non-null   float64
 9   Facing_direction  2924 non-null   object 
dtypes: float64(1), int64(2), object(7)
memory usage: 1.1+ MB
None


Describe the Data :
               Size     Area_sqft     Bathroom
count  14000.000000  14000.000000  6217.000000
mean       3.106643   3116.115571     2.193663
std        1.155827   2255.780445     0.964027
min        0.000000    150.000000     1.000000
25%        2.000000   1000.000000     2.000000
50%        3.000000   2741.000000     2.000000
75%        4.000000   5896.000000     3.000000
max        9.000000  14521.000000     9.000000


Decsribe the data including Object :
       Size_unit      Property_type Location Seller_type Rent_price  \
count      14000              14000    14000       14000      14000   
unique         3                  7      381           4        654   
top          BHK  Independent Floor    Saket       Agent     3.01 L   
freq       13621               9273      698       13490       2233   

             Status Facing_direction  
count         14000             2924  
unique            3                8  
top     Unfurnished        NorthEast  
freq           7573              932  


Unique value of Each Column :
-Size: 10
-Size_unit: 3
```

```
-Property_type: 7
-Location: 381
-Seller_type: 4
-Rent_price: 654
-Area_sqft: 547
-Status: 3
-Bathroom: 9
-Facing_direction: 8
```

Cleaning the Size of house

```python
print(F"Sum of house size = 0 : {(house["Size"]==0).sum()}")
```

```
Sum of house size = 0 : 4
```

```python
##### Removing rows where the 'Size' column has a value of 0, as such
entries are likely invalid or uninformative
initial_rows = house.shape[0]
print("Initial row count:", initial_rows)

# Filter out rows with Size = 0
house = house[house['Size'] != 0]

# Calculate and display the number of rows removed
rows_removed = initial_rows - house.shape[0]
print("Number of rows removed due to Size = 0:", rows_removed)
```

```
Initial row count: 14000
Number of rows removed due to Size = 0: 4
```

```python
#checkign the shape of data
house.shape
```

```
(13996, 10)
```

Cleaning the House Rent Price

```python
# Function to convert price strings to numeric values
def convert_price_into_numeric(price_str):
    # Remove commas from the string
    price_str = str(price_str).replace(',', '').strip().upper()

    # If price is in lakhs (e.g., '15L'), convert it to a numeric
value
    if 'L' in price_str:
        return float(price_str.replace('L', '')) * 100000

    # Otherwise, return the numeric value directly
    return float(price_str)

# Apply the function to the 'Rent_price' column
```

```
house['Rent_price'] =
house['Rent_price'].apply(convert_price_into_numeric)

# Print first 5 converted prices for verification
print("First 5 converted rent prices:\n", house['Rent_price'].head())
```

```
First 5 converted rent prices:
 0     8500.0
1    48000.0
2    20000.0
3    11000.0
4    20000.0
Name: Rent_price, dtype: float64
```

Cleanig the INFO

```
house.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 13996 entries, 0 to 13999
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Size              13996 non-null  int64
 1   Size_unit         13996 non-null  object
 2   Property_type     13996 non-null  object
 3   Location          13996 non-null  object
 4   Seller_type       13996 non-null  object
 5   Rent_price        13996 non-null  float64
 6   Area_sqft         13996 non-null  int64
 7   Status            13996 non-null  object
 8   Bathroom          6216 non-null   float64
 9   Facing_direction  2921 non-null   object
dtypes: float64(2), int64(2), object(6)
memory usage: 1.2+ MB
```

Handling the Missing Values

```
# Importing the KNN Imputer from scikit-learn
from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler

print("--- KNN Imputation for 'Bathroom' and related features ---")

# Selecting numerical features for KNN imputation (must be numeric and
relevant)
num_features_for_knn = ['Bathroom', 'Area_sqft', 'Size']
print(f"Selected numerical features for KNN: {num_features_for_knn}")
```

```
# Creating a subset of the DataFrame with only the selected numerical
columns
house_subset_knn = house[num_features_for_knn].copy()

# Storing original index and columns for use after imputation
original_index = house_subset_knn.index
original_columns = house_subset_knn.columns

# Scaling the data to normalize all features before KNN imputation
scaler = StandardScaler()
scaled_values_array = scaler.fit_transform(house_subset_knn)

# Creating a new DataFrame from the scaled values
house_scaled_for_knn = pd.DataFrame(scaled_values_array,
columns=original_columns, index=original_index)
print("\nSample of scaled data before KNN imputation:")
print(house_scaled_for_knn.head())

# Initializing KNNImputer with 5 neighbors and fitting it to the
scaled data
knn_imputer = KNNImputer(n_neighbors=11)
imputed_scaled_values_array =
knn_imputer.fit_transform(house_scaled_for_knn)
print("\nSample of scaled and imputed data (NumPy array from
KNNImputer):")
print(imputed_scaled_values_array[:5])

# Inversely transforming the imputed scaled data back to the original
scale
imputed_original_scale_array =
scaler.inverse_transform(imputed_scaled_values_array)

# Creating a DataFrame from the imputed data in original scale
house_imputed_original_scale =
pd.DataFrame(imputed_original_scale_array, columns=original_columns,
index=original_index)
print("\nSample of imputed data (back to original scale):")
print(house_imputed_original_scale.head())

# Updating the original DataFrame with the imputed values for the
selected columns
for col in original_columns:
    house[col] = house_imputed_original_scale[col]

# Final print statements to verify update and confirm missing values
are handled
print(f"\nOriginal DataFrame 'house' updated with KNN imputed values
for columns: {original_columns}.")
print("Missing values count after KNN imputation for selected
```

```
columns:")
print(house[num_features_for_knn].isnull().sum())
```

```
--- KNN Imputation for 'Bathroom' and related features ---
Selected numerical features for KNN: ['Bathroom', 'Area_sqft', 'Size']

Sample of scaled data before KNN imputation:
   Bathroom  Area_sqft      Size
0 -1.242059  -1.160012 -0.959103
1  0.840941  -0.929295 -0.093120
2 -0.200559  -1.022469 -0.959103
3 -1.242059  -1.049090 -0.093120
4 -0.200559  -0.805063 -0.093120

Sample of scaled and imputed data (NumPy array from KNNImputer):
[[-1.2420594  -1.16001191 -0.95910264]
 [ 0.84094107 -0.9292953  -0.09311976]
 [-0.20055917 -1.02246931 -0.95910264]
 [-1.2420594  -1.04909046 -0.09311976]
 [-0.20055917 -0.80506327 -0.09311976]]

Sample of imputed data (back to original scale):
   Bathroom  Area_sqft  Size
0       1.0      500.0   2.0
1       3.0     1020.0   3.0
2       2.0      810.0   2.0
3       1.0      750.0   3.0
4       2.0     1300.0   3.0

Original DataFrame 'house' updated with KNN imputed values for
columns: Index(['Bathroom', 'Area_sqft', 'Size'], dtype='object').
Missing values count after KNN imputation for selected columns:
Bathroom     0
Area_sqft    0
Size         0
dtype: int64
```

```
# This rounds bathroom values and converts them to integers
house['Bathroom'] = house['Bathroom'].round()

house.head()
```

```
   Size Size_unit      Property_type           Location     Seller_type
\
0   2.0       BHK  Independent Floor        Uttam Nagar  Verified Owner

1   3.0       BHK  Independent House         Model Town  Verified Owner

2   2.0       BHK          Apartment  Sector 13 Rohini  Verified Owner

3   3.0       BHK          Apartment          DLF Farms  Verified Owner
```

```
4   3.0       BHK  Independent Floor       laxmi nagar  Verified Owner
```

```
   Rent_price  Area_sqft           Status  Bathroom Facing_direction
0      8500.0      500.0  Semi-Furnished       1.0        NorthWest
1     48000.0     1020.0       Furnished       3.0            South
2     20000.0      810.0     Unfurnished       2.0              NaN
3     11000.0      750.0  Semi-Furnished       1.0              NaN
4     20000.0     1300.0       Furnished       2.0              NaN
```

```
print(f"Handling 'Facing_direction' with
{house['Facing_direction'].isnull().sum()} missing values
({house['Facing_direction'].isnull().mean()*100:.2f}%).")

fill_value = "Unknown"
house['Facing_direction'].fillna(fill_value, inplace=True)

print(f"Imputed 'Facing_direction' NaNs with '{fill_value}'.")
print(df['Facing_direction'].value_counts(dropna=False))
```

```
Handling 'Facing_direction' with 11075 missing values (79.13%).
Imputed 'Facing_direction' NaNs with 'Unknown'.
Facing_direction
NaN          11076
NorthEast      932
East           707
North          444
NorthWest      217
West           209
South          160
SouthEast      160
SouthWest       95
Name: count, dtype: int64
```

```
C:\Users\ashis\AppData\Local\Temp\ipykernel_21124\3137024577.py:4:
FutureWarning: A value is trying to be set on a copy of a DataFrame or
Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  house['Facing_direction'].fillna(fill_value, inplace=True)
```

```
print(house['Property_type'].value_counts())
wrong_value='ApartmentApartment'
correct_value='Apartment'
house['Property_type']=house['Property_type'].replace(wrong_value,
correct_value)
print(f"Replaced '{wrong_value}' with '{correct_value}' in
'Property_type'.")
print(house['Property_type'].value_counts())
```

```
Property_type
Independent Floor     9273
Apartment             2092
Villa                 1366
Independent House      824
Studio Apartment       373
Penthouse               67
ApartmentApartment       1
Name: count, dtype: int64
Replaced 'ApartmentApartment' with 'Apartment' in 'Property_type'.
Property_type
Independent Floor    9273
Apartment            2093
Villa                1366
Independent House     824
Studio Apartment      373
Penthouse              67
Name: count, dtype: int64
```

```
# Creating the Pivot Table for Facing Direction

pivot = pd.pivot_table(data = house, index = 'Facing_direction',
values = 'Size', aggfunc = 'count')

pivot
```

```
                   Size
Facing_direction
East                707
North               444
NorthEast           931
NorthWest           215
South               160
SouthEast           160
SouthWest            95
Unknown           11075
West                209
```

```
print(df['Size_unit'].value_counts())
wrong_value='BHKBHK'
correct_value='BHK'
```

```
df['Size_unit']=df['Size_unit'].replace(wrong_value, correct_value)
print(f"Replaced '{wrong_value}' with '{correct_value}' in
'Size_unit'.")
print(df['Size_unit'].value_counts())
```

```
Size_unit
BHK       13621
RK          373
BHKBHK        6
Name: count, dtype: int64
Replaced 'BHKBHK' with 'BHK' in 'Size_unit'.
Size_unit
BHK    13627
RK       373
Name: count, dtype: int64
```

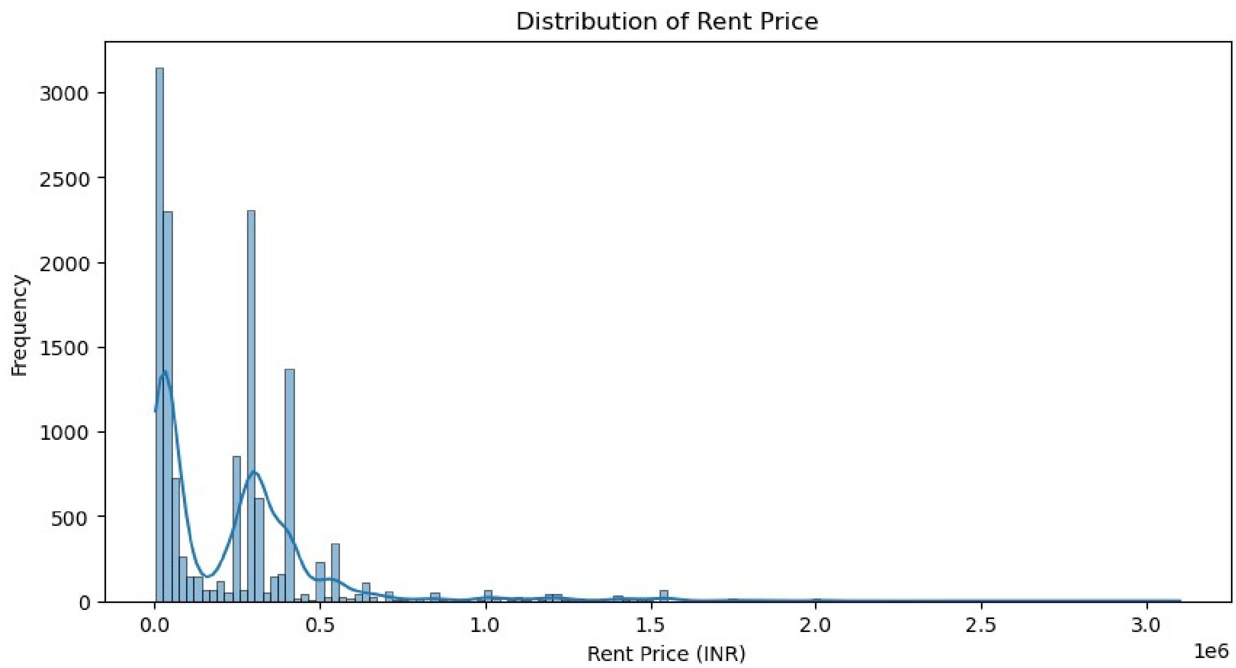
Exploratory Data Analysis

```
# Step III: Exploratory Data Analysis (EDA)
print("--- III. Exploratory Data Analysis (EDA) ---")

# ---------------------------------------------
# 1. Univariate Analysis (Distribution of individual features)
# ---------------------------------------------

# Distribution of Rent Price
print("\nAnalyzing target variable 'Rent_price':")
plt.figure(figsize=(10, 5))
sns.histplot(house['Rent_price'], kde=True)
plt.title('Distribution of Rent Price')
plt.xlabel('Rent Price (INR)')
plt.ylabel('Frequency')
plt.show()

# Checking skewness to decide on transformation if needed
print(f"Rent Price Skewness: {house['Rent_price'].skew():.2f}")
# If highly skewed, consider: house['Rent_price_log'] =
np.log1p(house['Rent_price'])

# Distribution of Area (sqft)
print("\nAnalyzing 'Area_sqft':")
plt.figure(figsize=(10, 5))
sns.histplot(house['Area_sqft'], kde=True)
plt.title('Distribution of Area (sqft)')
plt.xlabel('Area (sqft)')
plt.ylabel('Frequency')
plt.show()

# Count of Bathrooms
print("\nAnalyzing 'Bathroom' counts:")
```

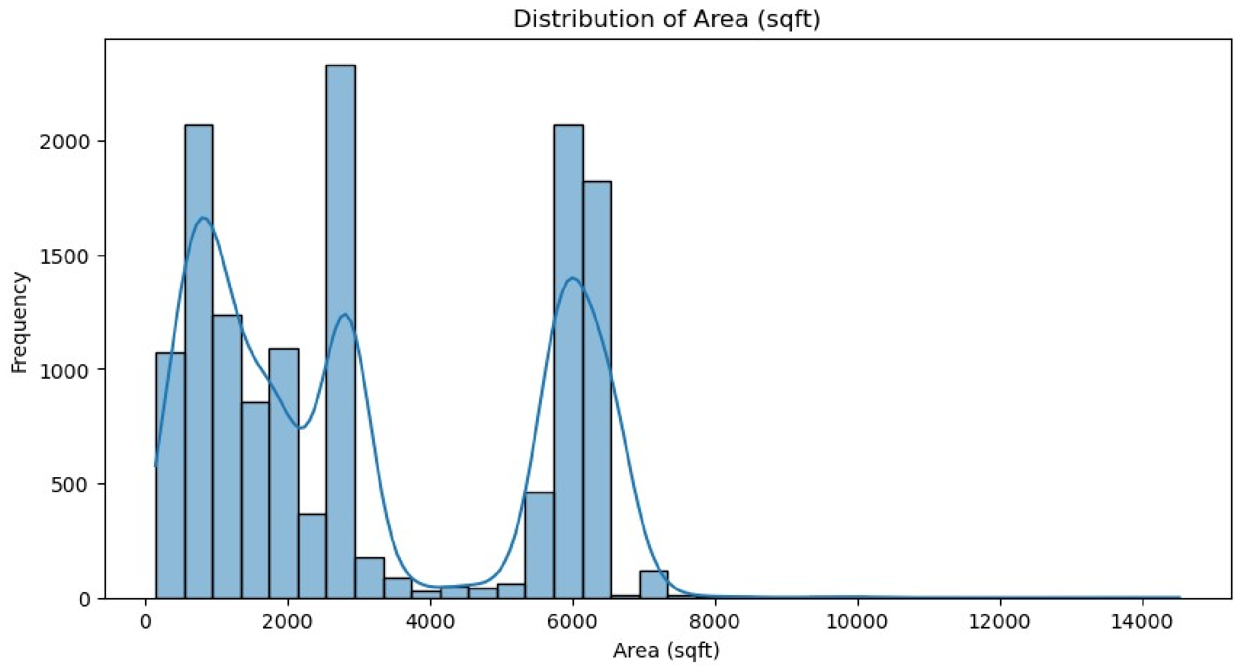
```python
plt.figure(figsize=(8, 5))
sns.countplot(x='Bathroom', data=house, palette='viridis')
plt.title('Count of Bathrooms')
plt.xlabel('Number of Bathrooms')
plt.ylabel('Number of Properties')
plt.show()

# Count of Property Types
print("\nAnalyzing 'Property_type':")
plt.figure(figsize=(12, 6))
house['Property_type'].value_counts().plot(kind='bar')
plt.title('Distribution of Property Types')
plt.xlabel('Property Type')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# ----------------------------------------------
# 2. Bivariate Analysis (Relationships between two variables)
# ----------------------------------------------

# Scatter plot of Rent Price vs. Area
print("\nRent Price vs. Area_sqft:")
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Area_sqft', y='Rent_price', data=house, alpha=0.5)
plt.title('Rent Price vs. Area (sqft)')
plt.xlabel('Area (sqft)')
plt.ylabel('Rent Price (INR)')
plt.show()

# Rent Price across Property Types using Boxplot
print("\nRent Price by Property Type:")
plt.figure(figsize=(12, 7))
sns.boxplot(x='Property_type', y='Rent_price', data=house,
palette='Set2')
plt.title('Rent Price by Property Type')
plt.xlabel('Property Type')
plt.ylabel('Rent Price (INR)')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Rent Price across Bathroom counts using Boxplot
print("\nRent Price by Number of Bathrooms:")
plt.figure(figsize=(10, 6))
sns.boxplot(x='Bathroom', y='Rent_price', data=house,
palette='coolwarm')
plt.title('Rent Price by Number of Bathrooms')
plt.xlabel('Number of Bathrooms')
```

```python
plt.ylabel('Rent Price (INR)')
plt.show()

# ---------------------------------------------
# 3. Correlation Analysis (Numerical Features Only)
# ---------------------------------------------

# Heatmap to visualize correlation between numerical variables
print("\nPerforming Correlation Analysis:")
numerical_df = house.select_dtypes(include=np.number)
plt.figure(figsize=(10, 8))
correlation_matrix = numerical_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f", linewidths=.5)
plt.title('Correlation Matrix of Numerical Features')
plt.show()

print("\nEDA complete. Review plots and statistics for insights.")
```

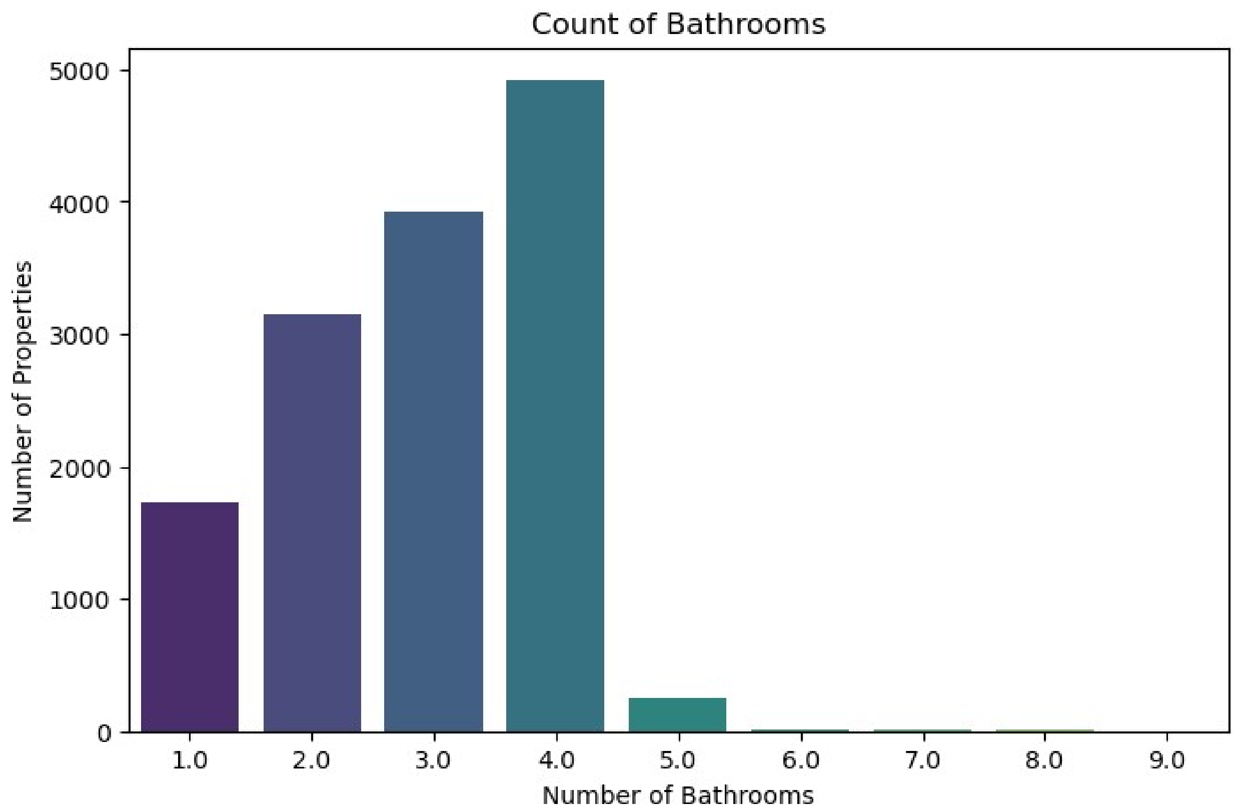
```
--- III. Exploratory Data Analysis (EDA) ---

Analyzing target variable 'Rent_price':
```



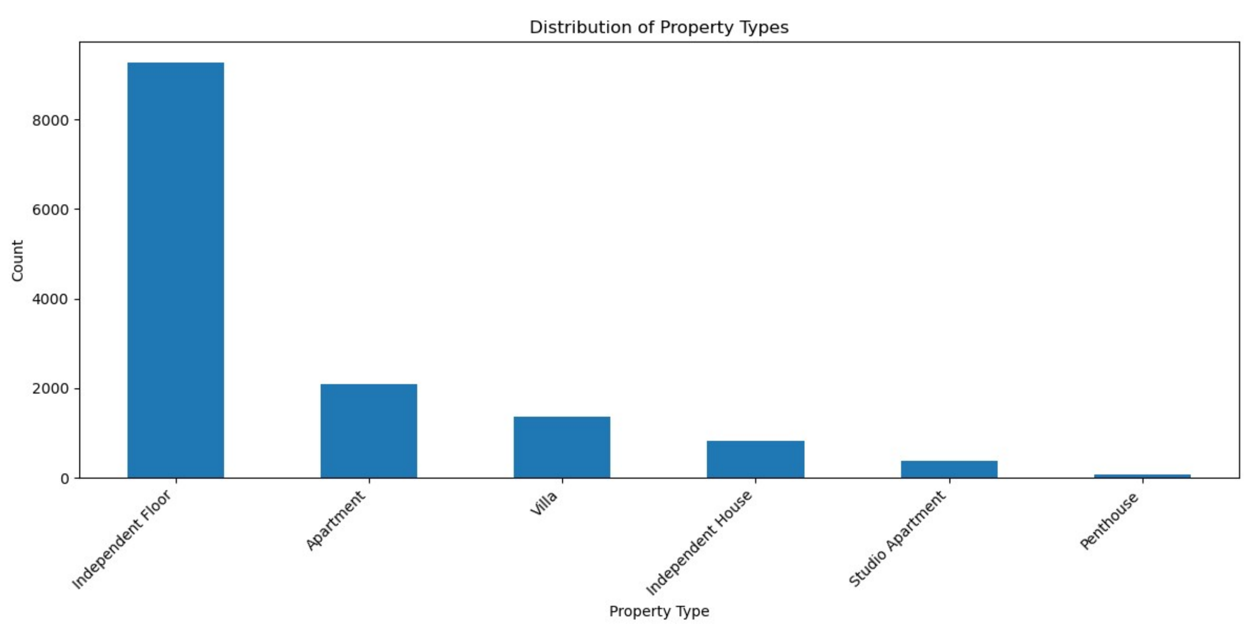

```
Rent Price Skewness: 2.93

Analyzing 'Area_sqft':
```



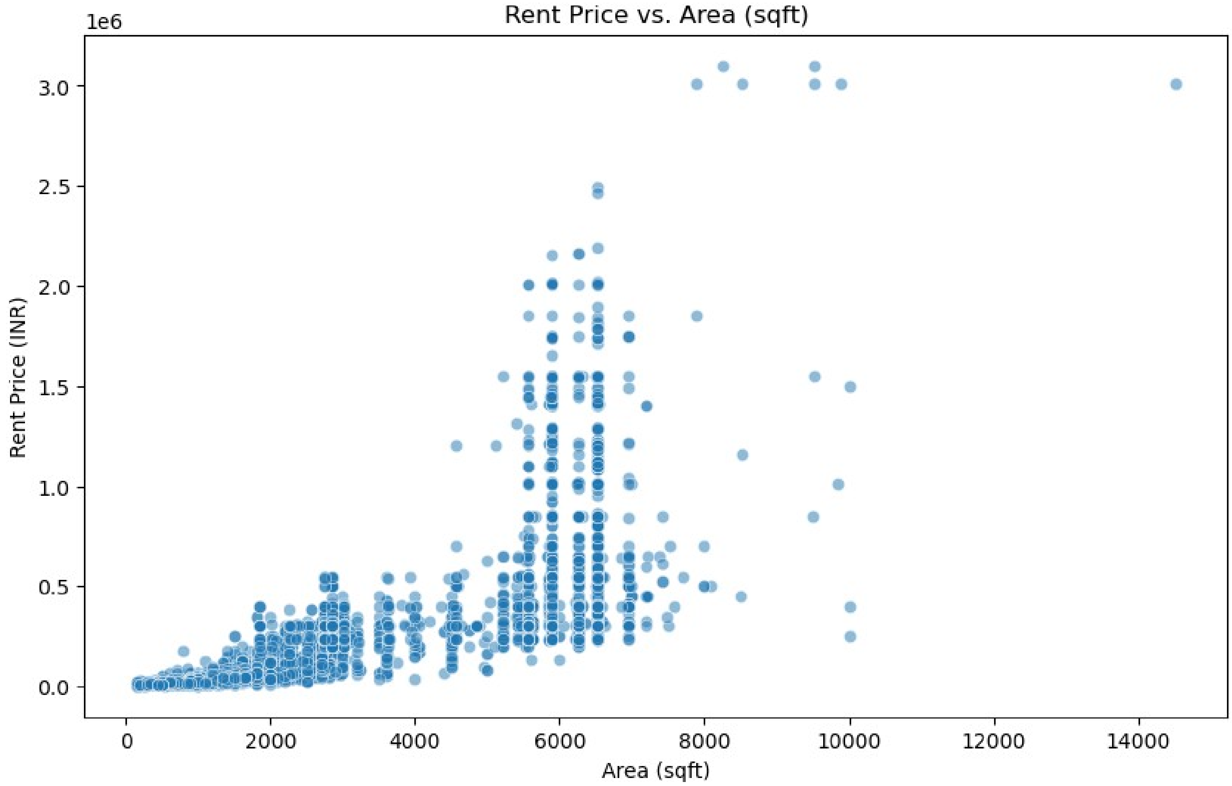

```
Analyzing 'Bathroom' counts:

C:\Users\ashis\AppData\Local\Temp\ipykernel_21124\2400713270.py:33:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='Bathroom', data=house, palette='viridis')
```



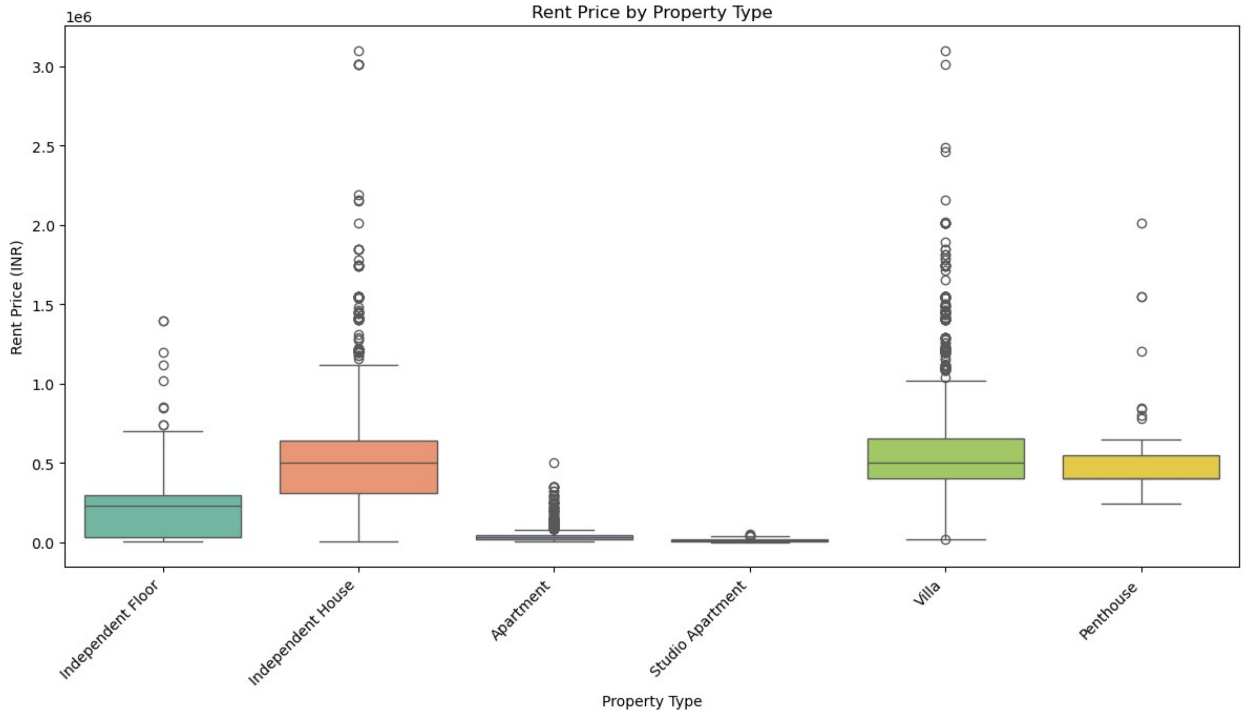

```
Analyzing 'Property_type':
```



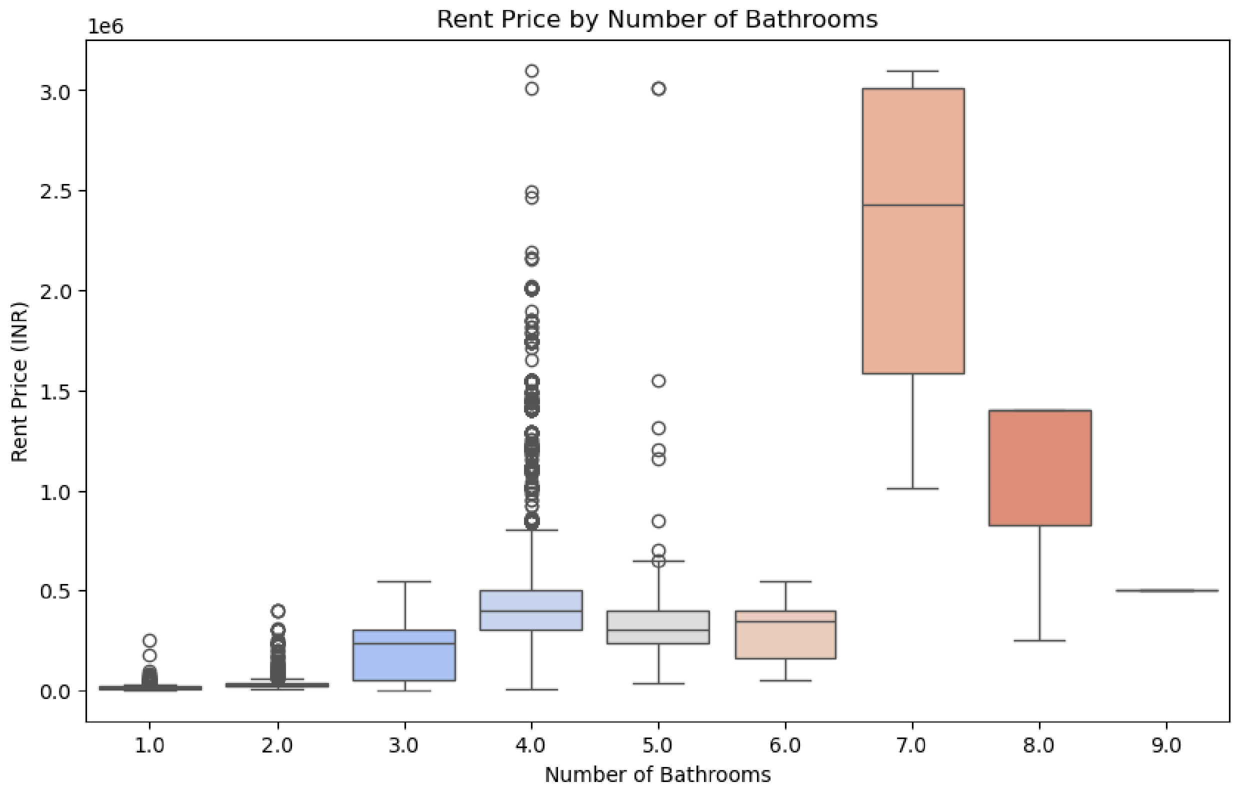

```
Rent Price vs. Area_sqft:
```



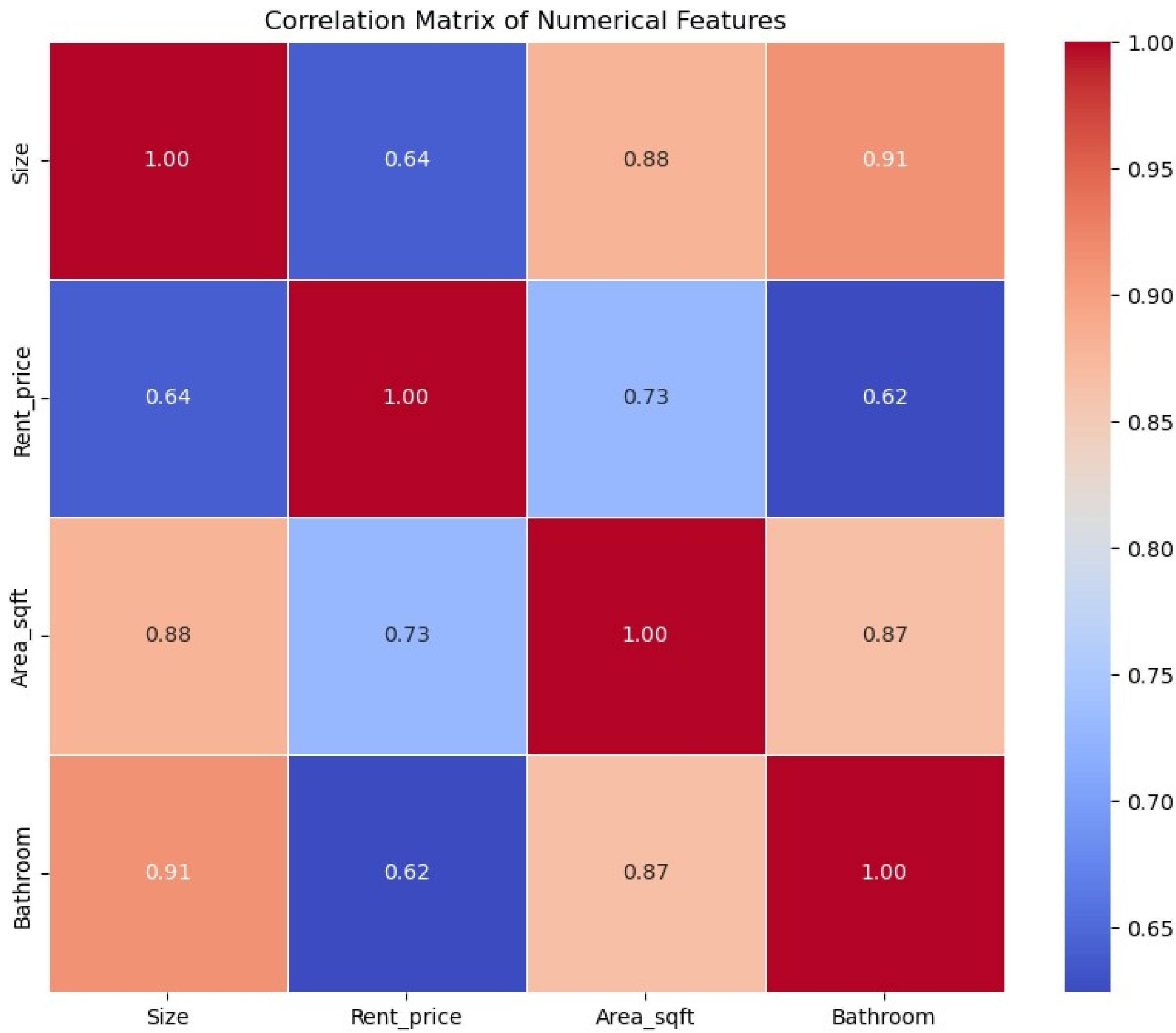

```
Rent Price by Property Type:

C:\Users\ashis\AppData\Local\Temp\ipykernel_21124\2400713270.py:66:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(x='Property_type', y='Rent_price', data=house,
palette='Set2')
```




```
Rent Price by Number of Bathrooms:

C:\Users\ashis\AppData\Local\Temp\ipykernel_21124\2400713270.py:77:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(x='Bathroom', y='Rent_price', data=house,
palette='coolwarm')
```




```
Performing Correlation Analysis:
```




```
EDA complete. Review plots and statistics for insights.

# Save a copy of the EDA-processed data
house_cleaned = house.copy()

house_cleaned.head()

   Size Size_unit      Property_type           Location     Seller_type
\
0   2.0       BHK  Independent Floor        Uttam Nagar  Verified Owner

1   3.0       BHK  Independent House         Model Town  Verified Owner

2   2.0       BHK          Apartment  Sector 13 Rohini  Verified Owner

3   3.0       BHK          Apartment          DLF Farms  Verified Owner
```

```
4   3.0       BHK  Independent Floor       laxmi nagar  Verified Owner


   Rent_price  Area_sqft           Status  Bathroom Facing_direction
0      8500.0      500.0  Semi-Furnished       1.0        NorthWest
1     48000.0     1020.0       Furnished       3.0            South
2     20000.0      810.0     Unfurnished       2.0          Unknown
3     11000.0      750.0  Semi-Furnished       1.0          Unknown
4     20000.0     1300.0       Furnished       2.0          Unknown
```

Diving the Data into Cateogrical and Continues Cols

```
house_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 13996 entries, 0 to 13999
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Size              13996 non-null  float64
 1   Size_unit         13996 non-null  object
 2   Property_type     13996 non-null  object
 3   Location          13996 non-null  object
 4   Seller_type       13996 non-null  object
 5   Rent_price        13996 non-null  float64
 6   Area_sqft         13996 non-null  float64
 7   Status            13996 non-null  object
 8   Bathroom          13996 non-null  float64
 9   Facing_direction  13996 non-null  object
dtypes: float64(4), object(6)
memory usage: 1.2+ MB
```

```
house_cleaned.groupby(['Location', 'Property_type'])
['Rent_price'].mean()
```

```
Location                         Property_type
AGCR Enclave                     Independent Floor    42000.000000
Abul Fazal Enclave Jamia Nagar   Independent Floor    14833.333333
Adarsh Nagar                     Independent Floor    15000.000000
Adchini                          Independent Floor    31000.000000
                                 Studio Apartment     13500.000000
                                                          ...
south delhi apartment sector 4   Apartment            35000.000000
vikaspuri                        Apartment            26000.000000
                                 Independent Floor    32700.000000
                                 Independent House    13000.000000
                                 Studio Apartment     11333.333333
Name: Rent_price, Length: 703, dtype: float64
```

```
house_cleaned['Location'].nunique()
```

```
381
```

Diving Data into Train and Test Module

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,
confusion_matrix, roc_auc_score
from sklearn.neighbors import KNeighborsClassifier

from category_encoders import TargetEncoder
from category_encoders import CatBoostEncoder

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer


# --- Define Features (X) and Target (y) ---
X = house_cleaned.drop('Rent_price', axis=1)
y = house_cleaned['Rent_price']

# ---  Split Data into Training and Testing sets  ---
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# ---  Manual Preprocessing ---

# Create copies to avoid modifying original X_train, X_test slices
directly during transformations
X_train_processed = X_train.copy()
X_test_processed = X_test.copy()


# ---  CatBoostEncode 'Location' ---
print("\n--- Applying CatBoostEncoder for 'Location' ---")
loc_encoder = CatBoostEncoder(cols=['Location'], sigma=0.05,
random_state=42)

# Fit on X_train and y_train
loc_encoder.fit(X_train, y_train)

X_train_processed = loc_encoder.transform(X_train.copy())
X_test_processed = loc_encoder.transform(X_test.copy())
print("X_train_processed head after CatBoostEncoding 'Location':")
print(X_train_processed.head())
print("Data type of 'Location' in X_train_processed:",
X_train_processed['Location'].dtype)
```

```
# ---  One-Hot Encode other categorical features ---
print("\n--- Applying OneHotEncoder for other categoricals ---")
ohe_categorical_features = ['Property_type', 'Seller_type',
'Size_unit', 'Status', 'Facing_direction']


ohe = OneHotEncoder(handle_unknown='ignore', sparse_output=False)

# Fit OHE on X_train_processed for the categorical columns
ohe.fit(X_train_processed[ohe_categorical_features])

# Get feature names for OHE columns
ohe_feature_names =
ohe.get_feature_names_out(ohe_categorical_features)

# Transform training data
X_train_ohe_features =
ohe.transform(X_train_processed[ohe_categorical_features])
X_train_ohe_df = pd.DataFrame(X_train_ohe_features,
columns=ohe_feature_names, index=X_train_processed.index)

# Transform test data
X_test_ohe_features =
ohe.transform(X_test_processed[ohe_categorical_features])
X_test_ohe_df = pd.DataFrame(X_test_ohe_features,
columns=ohe_feature_names, index=X_test_processed.index)

# Drop original categorical columns from X_train_processed and
X_test_processed
X_train_processed.drop(columns=ohe_categorical_features, inplace=True)
X_test_processed.drop(columns=ohe_categorical_features, inplace=True)

# Concatenate OHE features
X_train_processed = pd.concat([X_train_processed, X_train_ohe_df],
axis=1)
X_test_processed = pd.concat([X_test_processed, X_test_ohe_df],
axis=1)

print(f"X_train_processed shape after OHE: {X_train_processed.shape}")


# --- StandardScale numerical features ---

print("\n--- Applying StandardScaler for numerical features ---")
numerical_features_to_scale = ['Size', 'Bathroom', 'Area_sqft',
'Location']

# Initialize StandardScaler
scaler = StandardScaler()
```

```python
scaler.fit(X_train_processed[numerical_features_to_scale])

# Transform both training and test data for these columns
X_train_processed[numerical_features_to_scale] =
scaler.transform(X_train_processed[numerical_features_to_scale])
X_test_processed[numerical_features_to_scale] =
scaler.transform(X_test_processed[numerical_features_to_scale])

print("X_train_processed head after Scaling (sample of scaled
numericals):")
print(X_train_processed[numerical_features_to_scale].head())


# --- Verification ---
print("\n--- Final Processed Data Samples ---")
print("X_train_processed head:")
print(X_train_processed.head())
print(f"X_train_processed shape: {X_train_processed.shape}")
print("\nX_test_processed head:")
print(X_test_processed.head())
print(f"X_test_processed shape: {X_test_processed.shape}")
```

```
--- Applying CatBoostEncoder for 'Location' ---
X_train_processed head after CatBoostEncoding 'Location':
       Size Size_unit      Property_type       Location Seller_type  \
10405   3.0       BHK          Apartment   49208.153917       Agent
3713    3.0       BHK          Apartment  253542.391365       Agent
3574    3.0       BHK          Apartment   41548.440570       Agent
6928    4.0       BHK  Independent House  253542.391365       Agent
6226    5.0       BHK  Independent Floor  327077.629194       Agent

       Area_sqft          Status  Bathroom Facing_direction
10405     1275.0  Semi-Furnished       3.0          Unknown
3713      2100.0  Semi-Furnished       2.0             East
3574      1700.0  Semi-Furnished       3.0             East
6928      5896.0     Unfurnished       4.0          Unknown
6226      6952.0     Unfurnished       4.0          Unknown
Data type of 'Location' in X_train_processed: float64

--- Applying OneHotEncoder for other categoricals ---
X_train_processed shape after OHE: (11196, 29)

--- Applying StandardScaler for numerical features ---
X_train_processed head after Scaling (sample of scaled numericals):
           Size  Bathroom  Area_sqft  Location
10405 -0.091250  0.071250  -0.815980 -0.861729
3713  -0.091250 -0.855251  -0.449017  0.104689
3574  -0.091250  0.071250  -0.626938 -0.897956
6928   0.775274  0.997752   1.239458  0.104689
```

```
6226   1.641797  0.997752   1.709171  0.452481

--- Final Processed Data Samples ---
X_train_processed head:
           Size  Location  Area_sqft  Bathroom
Property_type_Apartment  \
10405 -0.091250 -0.861729  -0.815980  0.071250
1.0
3713  -0.091250  0.104689  -0.449017 -0.855251
1.0
3574  -0.091250 -0.897956  -0.626938  0.071250
1.0
6928   0.775274  0.104689   1.239458  0.997752
0.0
6226   1.641797  0.452481   1.709171  0.997752
0.0

       Property_type_Independent Floor  Property_type_Independent
House  \
10405                              0.0
0.0
3713                               0.0
0.0
3574                               0.0
0.0
6928                               0.0
1.0
6226                               1.0
0.0

       Property_type_Penthouse  Property_type_Studio Apartment  \
10405                      0.0                             0.0
3713                       0.0                             0.0
3574                       0.0                             0.0
6928                       0.0                             0.0
6226                       0.0                             0.0

       Property_type_Villa  ...  Status_Unfurnished
Facing_direction_East  \
10405                  0.0  ...                 0.0
0.0
3713                   0.0  ...                 0.0
1.0
3574                   0.0  ...                 0.0
1.0
6928                   0.0  ...                 1.0
0.0
6226                   0.0  ...                 1.0
0.0
```

```
       Facing_direction_North  Facing_direction_NorthEast  \
10405                     0.0                         0.0
3713                      0.0                         0.0
3574                      0.0                         0.0
6928                      0.0                         0.0
6226                      0.0                         0.0

       Facing_direction_NorthWest  Facing_direction_South  \
10405                         0.0                     0.0
3713                          0.0                     0.0
3574                          0.0                     0.0
6928                          0.0                     0.0
6226                          0.0                     0.0

       Facing_direction_SouthEast  Facing_direction_SouthWest  \
10405                         0.0                         0.0
3713                          0.0                         0.0
3574                          0.0                         0.0
6928                          0.0                         0.0
6226                          0.0                         0.0

       Facing_direction_Unknown  Facing_direction_West
10405                       1.0                    0.0
3713                        0.0                    0.0
3574                        0.0                    0.0
6928                        1.0                    0.0
6226                        1.0                    0.0

[5 rows x 29 columns]
X_train_processed shape: (11196, 29)

X_test_processed head:
           Size  Location  Area_sqft  Bathroom
Property_type_Apartment  \
2901  -0.091250 -0.897717  -0.626938 -0.855251
1.0
3144  -0.957773 -0.905044  -0.960541 -0.855251
0.0
12275 -0.091250  0.237195  -0.162118  0.071250
0.0
3858  -1.824297 -0.991035  -1.227423 -1.781753
0.0
8460  -0.091250  0.428563  -0.112745  0.071250
0.0

       Property_type_Independent Floor  Property_type_Independent
House  \
2901                               0.0
0.0
3144                               1.0
```

```
0.0
12275                            1.0
0.0
3858                             0.0
0.0
8460                             1.0
0.0

       Property_type_Penthouse  Property_type_Studio Apartment  \
2901                       0.0                             0.0
3144                       0.0                             0.0
12275                      0.0                             0.0
3858                       0.0                             1.0
8460                       0.0                             0.0

       Property_type_Villa  ...  Status_Unfurnished
Facing_direction_East  \
2901                   0.0  ...                 0.0
1.0
3144                   0.0  ...                 0.0
0.0
12275                  0.0  ...                 1.0
0.0
3858                   0.0  ...                 0.0
0.0
8460                   0.0  ...                 1.0
0.0

       Facing_direction_North  Facing_direction_NorthEast  \
2901                      0.0                         0.0
3144                      0.0                         0.0
12275                     0.0                         0.0
3858                      0.0                         0.0
8460                      0.0                         0.0

       Facing_direction_NorthWest  Facing_direction_South  \
2901                          0.0                     0.0
3144                          0.0                     0.0
12275                         0.0                     0.0
3858                          0.0                     1.0
8460                          0.0                     0.0

       Facing_direction_SouthEast  Facing_direction_SouthWest  \
2901                          0.0                         0.0
3144                          0.0                         0.0
12275                         0.0                         0.0
3858                          0.0                         0.0
8460                          0.0                         0.0

       Facing_direction_Unknown  Facing_direction_West
```

```
2901                        0.0                      0.0
3144                        1.0                      0.0
12275                       1.0                      0.0
3858                        0.0                      0.0
8460                        1.0                      0.0

[5 rows x 29 columns]
X_test_processed shape: (2800, 29)
```

```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
```

```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\ashis\anaconda3\
lib\site-packages (3.0.0)
Requirement already satisfied: numpy in c:\users\ashis\anaconda3\lib\
site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\ashis\anaconda3\lib\
site-packages (from xgboost) (1.13.1)
```

```
import xgboost as xgb
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import mean_squared_error, r2_score,
mean_absolute_error, silhouette_score, davies_bouldin_score


from sklearn.svm import SVR


# print("\n--- Hyperparameter Tuning for RandomForestRegressor ---")
# scoring_metric = 'neg_root_mean_squared_error' # Define if not
already
# rf_param_grid = {
#     'n_estimators': [100, 200, 300],       # Number of trees
#     'max_depth': [10, 15, 20, None],      # Max depth of trees (None
means full depth)
#     'min_samples_split': [2, 5, 10],      # Min samples to split an
internal node
#     'min_samples_leaf': [1, 2, 4],        # Min samples at a leaf
node
#     'max_features': ['sqrt', 'log2', 0.7] # Options for number of
features to consider. 0.7 means 70% of features.

#     }
# # Initialize RandomForestRegressor
```

```
# rf = RandomForestRegressor(random_state=42, n_jobs=-1)
# grid_search_rf =
GridSearchCV(estimator=rf,param_grid=rf_param_grid,cv=4,scoring=scorin
g_metric,verbose=2, n_jobs=-1)

# print("Starting GridSearchCV for RandomForestRegressor... This may
take some time.")
# # Fit GridSearchCV on the training data
# grid_search_rf.fit(X_train_processed, y_train)
# # Get the best parameters and the best score
# print("\nBest parameters found by GridSearchCV for Random Forest:")
# print(grid_search_rf.best_params_)
# best_rmse_rf_cv = -grid_search_rf.best_score_
# print(f"\nBest Cross-Validated RMSE for Random Forest:
{best_rmse_rf_cv:.2f}")
# # Get the best estimator
# best_rf_model = grid_search_rf.best_estimator_

print("--- Modeling ---")

# Define supervised models
models_supervised = {
    "1. Linear Regression": LinearRegression(),
    "2. Ridge Regression (L2)": Ridge(alpha=1.0, random_state=42),
    "3. Lasso Regression (L1)": Lasso(alpha=0.1, random_state=42,
max_iter=
                                      60000),
    "4. Decision Tree": DecisionTreeRegressor(random_state=42,
max_depth=5, min_samples_leaf=1, min_samples_split=2),
    "5. Random Forest": RandomForestRegressor(
        n_estimators=100, max_features=0.7, random_state=42, n_jobs=-
1,
        max_depth=10, min_samples_split=10, min_samples_leaf=1
    ),
    "6. Gradient Boosting": GradientBoostingRegressor(
        n_estimators=200, learning_rate=0.05, max_depth=4,
random_state=42,
        min_samples_leaf=2, subsample=0.8, min_samples_split=2
    ),
    "7. SVR (RBF Kernel)": SVR(kernel='rbf', C=1.0, epsilon=0.1),
    "8. MLP Regressor": MLPRegressor(
        hidden_layer_sizes=(64, 32), activation='relu', solver='adam',
        max_iter=500, random_state=42, early_stopping=True,
alpha=0.001
    ),
    "9. XGBoost": xgb.XGBRegressor(
        objective='reg:squarederror', n_estimators=100,
learning_rate=0.05,
        max_depth=5, colsample_bytree=0.9, reg_alpha=0, reg_lambda=1,
        subsample=0.9, gamma=0, random_state=42, n_jobs=-1
```

```python
    )
}

results_supervised = {}
trained_supervised_models = {}

print("\nTraining and evaluating models...")

for name, model in models_supervised.items():
    print(f"Training {name}...")

    # Train model
    model.fit(X_train_processed, y_train)
    trained_supervised_models[name] = model

    # Predictions
    y_pred_train = model.predict(X_train_processed)
    y_pred_test = model.predict(X_test_processed)

    # Evaluation metrics
    mae_train = mean_absolute_error(y_train, y_pred_train)
    rmse_train = np.sqrt(mean_squared_error(y_train, y_pred_train))
    r2_train = r2_score(y_train, y_pred_train)

    mae_test = mean_absolute_error(y_test, y_pred_test)
    rmse_test = np.sqrt(mean_squared_error(y_test, y_pred_test))
    r2_test = r2_score(y_test, y_pred_test)

    # Save results
    results_supervised[name] = {
        "MAE Train": mae_train,
        "RMSE Train": rmse_train,
        "R2 Train": r2_train,
        "MAE Test": mae_test,
        "RMSE Test": rmse_test,
        "R2 Test": r2_test
    }

    print(f"  {name} - Train RMSE: {rmse_train:.2f}, Test RMSE:
{rmse_test:.2f}, Test R2: {r2_test:.4f}")

# Compile results
results_supervised_df =
pd.DataFrame(results_supervised).T.sort_values(by="RMSE Test")

print("\n--- Model Performance Comparison (sorted by Test RMSE) ---")
print(results_supervised_df)
```

```
--- Modeling ---

Training and evaluating models...
```

```
Training 1. Linear Regression...
  1. Linear Regression - Train RMSE: 120481.35, Test RMSE: 144390.23,
Test R2: 0.7546
Training 2. Ridge Regression (L2)...
  2. Ridge Regression (L2) - Train RMSE: 120481.56, Test RMSE:
144386.88, Test R2: 0.7546
Training 3. Lasso Regression (L1)...
  3. Lasso Regression (L1) - Train RMSE: 120481.35, Test RMSE:
144390.18, Test R2: 0.7546
Training 4. Decision Tree...
  4. Decision Tree - Train RMSE: 82880.33, Test RMSE: 99832.92, Test
R2: 0.8827
Training 5. Random Forest...
  5. Random Forest - Train RMSE: 71794.64, Test RMSE: 92618.46, Test
R2: 0.8990
Training 6. Gradient Boosting...
  6. Gradient Boosting - Train RMSE: 73051.62, Test RMSE: 92892.89,
Test R2: 0.8984
Training 7. SVR (RBF Kernel)...
  7. SVR (RBF Kernel) - Train RMSE: 265492.93, Test RMSE: 290649.22,
Test R2: 0.0058
Training 8. MLP Regressor...
  8. MLP Regressor - Train RMSE: 115170.41, Test RMSE: 138001.55, Test
R2: 0.7759
Training 9. XGBoost...
  9. XGBoost - Train RMSE: 73795.75, Test RMSE: 96457.97, Test R2:
0.8905

--- Model Performance Comparison (sorted by Test RMSE) ---
                              MAE Train     RMSE Train  R2 Train  \
5. Random Forest            36307.942176   71794.637176  0.927517
6. Gradient Boosting        38681.962659   73051.621604  0.924957
9. XGBoost                  38524.140906   73795.746836  0.923420
4. Decision Tree            43938.863366   82880.330954  0.903405
8. MLP Regressor            58301.936469  115170.405355  0.813476
2. Ridge Regression (L2)    68118.970953  120481.556104  0.795876
3. Lasso Regression (L1)    68122.070880  120481.348014  0.795877
1. Linear Regression        68122.045381  120481.347949  0.795877
7. SVR (RBF Kernel)        186423.780104  265492.928628  0.008805

                               MAE Test      RMSE Test   R2 Test
5. Random Forest            41200.547314   92618.462007  0.899042
6. Gradient Boosting        42468.176264   92892.888141  0.898442
9. XGBoost                  42286.799188   96457.971063  0.890498
4. Decision Tree            47067.024388   99832.915298  0.882701
8. MLP Regressor            62749.648685  138001.547947  0.775862
2. Ridge Regression (L2)    73061.409704  144386.876104  0.754640
3. Lasso Regression (L1)    73070.986555  144390.176933  0.754629
```

```
1. Linear Regression       73070.948869  144390.226864  0.754629
7. SVR (RBF Kernel)       190533.757926  290649.215233  0.005772
```

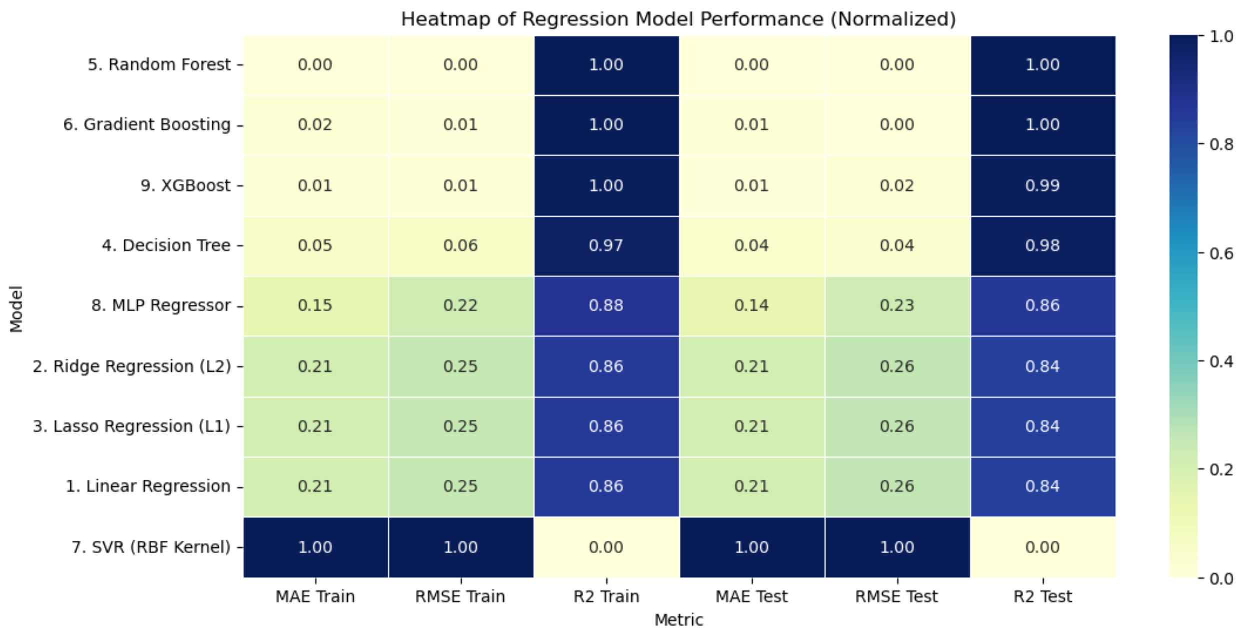
```
for top in range(0, 4):
    best_model_name_from_results = results_supervised_df.index[top]
    best_model =
trained_supervised_models[best_model_name_from_results]

    # Extract feature importances (with underscore)
    importances = best_model.feature_importances_

    final_feature_names = X_train_processed.columns

    feature_importance_df = pd.DataFrame({
        'feature': final_feature_names,
        'importance': importances
    })

    feature_importance_df =
feature_importance_df.sort_values(by='importance', ascending=False)

    print(f"\n--- Top 10 Feature Importances
({best_model_name_from_results}) ---")
    print(feature_importance_df.head(10))

print("\nModeling complete.")
```

```
--- Top 10 Feature Importances (5. Random Forest) ---
                             feature  importance
2                          Area_sqft    0.429224
1                           Location    0.372669
5   Property_type_Independent Floor    0.083639
19                Status_Unfurnished    0.057542
3                           Bathroom    0.016796
9                Property_type_Villa    0.015893
6   Property_type_Independent House    0.009883
0                               Size    0.009591
4            Property_type_Apartment    0.001650
17                  Status_Furnished    0.000891

--- Top 10 Feature Importances (6. Gradient Boosting) ---
                             feature  importance
2                          Area_sqft    0.530393
1                           Location    0.366783
5   Property_type_Independent Floor    0.082535
0                               Size    0.008802
19                Status_Unfurnished    0.003229
6   Property_type_Independent House    0.001967
3                           Bathroom    0.001661
```

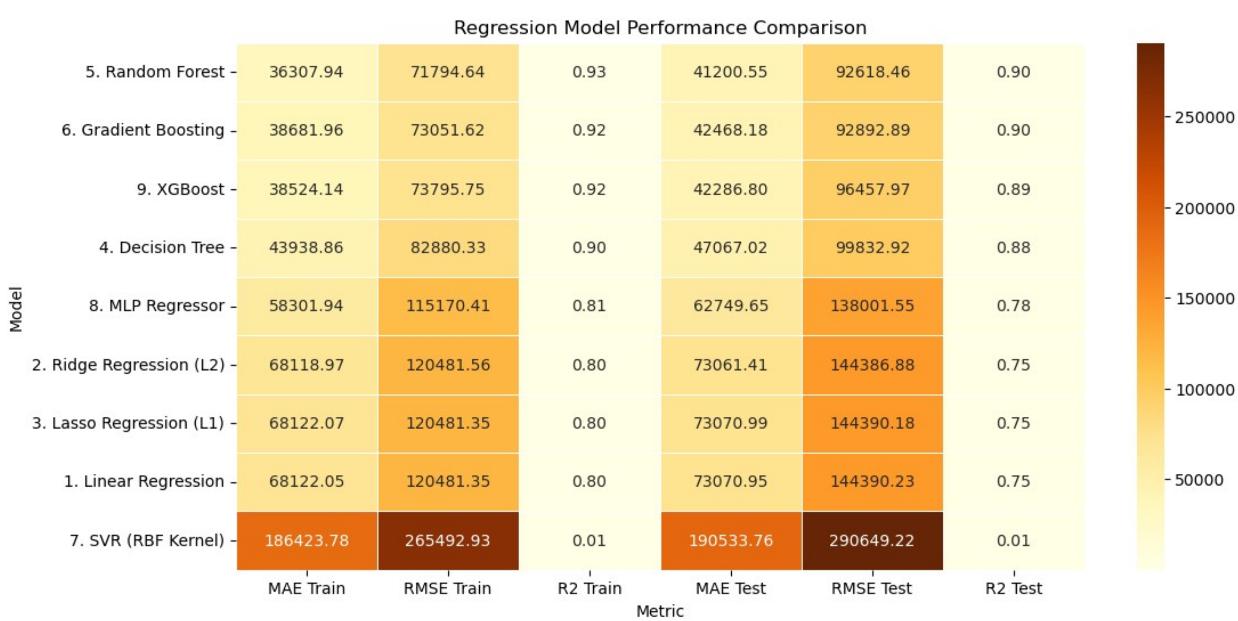
```
9                Property_type_Villa    0.001177
4            Property_type_Apartment    0.001121
7            Property_type_Penthouse    0.000924

--- Top 10 Feature Importances (9. XGBoost) ---
                            feature  importance
2                         Area_sqft    0.351318
5   Property_type_Independent Floor    0.221674
1                          Location    0.204920
9               Property_type_Villa    0.053129
19               Status_Unfurnished    0.037912
4           Property_type_Apartment    0.036171
6   Property_type_Independent House    0.028222
3                          Bathroom    0.026190
0                              Size    0.014244
18           Status_Semi-Furnished    0.006390

--- Top 10 Feature Importances (4. Decision Tree) ---
                            feature  importance
2                         Area_sqft    0.550488
1                          Location    0.355052
5   Property_type_Independent Floor    0.082803
4           Property_type_Apartment    0.004353
0                              Size    0.003881
9               Property_type_Villa    0.001585
6   Property_type_Independent House    0.000738
19               Status_Unfurnished    0.000718
3                          Bathroom    0.000381
27          Facing_direction_Unknown    0.000000

Modeling complete.
```

Heatmap of Regression Model Performance (Normalized)

```
# Normalize metrics for better comparison
results_normalized = results_supervised_df.copy()
for col in results_normalized.columns:
    results_normalized[col] = (results_normalized[col] - 
results_normalized[col].min()) / (results_normalized[col].max() - 
results_normalized[col].min())

plt.figure(figsize=(12, 6))
sns.heatmap(results_normalized, annot=True, cmap="YlGnBu", 
linewidths=0.5, fmt=".2f")
plt.title("Heatmap of Regression Model Performance (Normalized)")
plt.ylabel("Model")
plt.xlabel("Metric")
plt.show()
```




```python
final_feature_names = X_train_processed.columns  # if it's a DataFrame


# Regrssion Model Performance Comparison
plt.figure(figsize=(12, 6))
sns.heatmap(results_supervised_df, annot=True, cmap="YlOrBr",
fmt=".2f", linewidths=0.5)
plt.title("Regression Model Performance Comparison")
plt.ylabel("Model")
plt.xlabel("Metric")
plt.show()
```



Checking the Our Model on the New Data

```
house_cleaned.head()
```

```
   Size Size_unit      Property_type          Location     Seller_type  \
0   2.0       BHK  Independent Floor       Uttam Nagar  Verified Owner   
1   3.0       BHK  Independent House        Model Town  Verified Owner   
2   2.0       BHK          Apartment  Sector 13 Rohini  Verified Owner   
3   3.0       BHK          Apartment         DLF Farms  Verified Owner   
4   3.0       BHK  Independent Floor       laxmi nagar  Verified Owner   

   Rent_price  Area_sqft           Status  Bathroom Facing_direction  
0      8500.0      500.0  Semi-Furnished       1.0        NorthWest  
1     48000.0     1020.0       Furnished       3.0            South  
2     20000.0      810.0     Unfurnished       2.0          Unknown  
3     11000.0      750.0  Semi-Furnished       1.0          Unknown  
4     20000.0     1300.0       Furnished       2.0          Unknown  
```

```python
# Step 1: Capture user inputs
user_input = {
    'Size': int(input("Enter your House Size Here: ")),
    'Area_sqft': int(input("Enter your House Area (in sqft): ")),
    'Seller_type' :input("Enter Your Seller Type : "),
    'Size_unit' :input("Enter Your Size Unit : "),
    'Bathroom': int(input("Enter Number of Bathrooms: ")),
    'Location': input("Enter your Location: "),
    'Property_type': input("Enter Property Type (e.g. Apartment, 
Villa): "),
    'Status': input("Enter Furnishing Status (Furnished, Semi-
Furnished, Unfurnished): "),
    'Facing_direction': input("Enter Facing Direction (e.g. East, 
West): ")
}

# Step 2: Convert to DataFrame
input_df = pd.DataFrame([user_input])
```

```
Enter your House Size Here:  2
Enter your House Area (in sqft):  580
Enter Your Seller Type :  Owner
Enter Your Size Unit :  BHK
Enter Number of Bathrooms:  1
Enter your Location:  Dwarka Mor
Enter Property Type (e.g. Apartment, Villa):  Apartment
Enter Furnishing Status (Furnished, Semi-Furnished, Unfurnished):
```

```
Unfurnished
Enter Facing Direction (e.g. East, West):  Unknown


# input_dict={'Property_type':'Apartment', 'Seller_type':'Agent',
'Size_unit':'RK','Status':'Unfurnished','Facing_direction':'East','Siz
e' :1,'Bathroom':1,'Area_sqft':100,'Location':'Lajpat Nagar' }
input_df = pd.DataFrame([user_input])

input_df = input_df[X.columns]

input_df_processed = input_df.copy()

input_df_processed = loc_encoder.transform(input_df_processed)

input_ohe_features =
ohe.transform(input_df_processed[ohe_categorical_features])
input_ohe_df = pd.DataFrame(input_ohe_features,
columns=ohe_feature_names, index=input_df_processed.index)

input_df_processed.drop(columns=ohe_categorical_features,
inplace=True)
input_df_processed = pd.concat([input_df_processed, input_ohe_df],
axis=1)

input_df_processed[numerical_features_to_scale] =
scaler.transform(input_df_processed[numerical_features_to_scale])




print("\nProcessed input data for prediction:")
print(input_df_processed)
print(f"Shape of processed input: {input_df_processed.shape}")


Processed input data for prediction:
       Size  Location  Area_sqft  Bathroom  Property_type_Apartment  \
0 -0.957773 -1.002791  -1.125118 -1.781753                      1.0

   Property_type_Independent Floor  Property_type_Independent House  \
0                              0.0                              0.0

   Property_type_Penthouse  Property_type_Studio Apartment  \
0                      0.0                             0.0

   Property_type_Villa  ...  Status_Unfurnished  Facing_direction_East
\
0                  0.0  ...                 1.0                    0.0
```

```
   Facing_direction_North  Facing_direction_NorthEast  \
0                     0.0                         0.0

   Facing_direction_NorthWest  Facing_direction_South  \
0                         0.0                     0.0

   Facing_direction_SouthEast  Facing_direction_SouthWest  \
0                         0.0                         0.0

   Facing_direction_Unknown  Facing_direction_West
0                       1.0                   0.0

[1 rows x 29 columns]
Shape of processed input: (1, 29)
```

```
# Select Model and Predict
print("\nAvailable models:")
for i, model_name in enumerate(trained_supervised_models.keys()):
    print(f" {model_name}")

while True:
    try:
        choice = int(input(f"Select a model by number (1-
{len(trained_supervised_models)}): "))
        if 1 <= choice <= len(trained_supervised_models):
            selected_model_name =
list(trained_supervised_models.keys())[choice-1]
            break
        else:
            print("Invalid choice. Please enter a number from the
list.")
    except ValueError:
        print("Invalid input. Please enter a number.")

selected_model = trained_supervised_models[selected_model_name]
print(f"\nUsing model: {selected_model_name}")

prediction = selected_model.predict(input_df_processed)



print("Pridicting The Rent Price on your Inputs :")

print(f"\nPredicted Rent Price: {prediction[0]:.2f}")
```

```
Available models:
 1. Linear Regression
 2. Ridge Regression (L2)
 3. Lasso Regression (L1)
```

```
 4. Decision Tree
 5. Random Forest
 6. Gradient Boosting
 7. SVR (RBF Kernel)
 8. MLP Regressor
 9. XGBoost

Select a model by number (1-9):  5


Using model: 5. Random Forest
Pridicting The Rent Price on your Inputs :

Predicted Rent Price: 11653.00
```

```
input_df
```

```
   Size Size_unit Property_type    Location Seller_type  Area_sqft  \
0     2       BHK     Apartment  Dwarka Mor       Owner        580

        Status  Bathroom Facing_direction
0  Unfurnished         1          Unknown
```

```
house_cleaned.shape
```

```
(13996, 10)
```